Design for diagnostics and prognostics

Niculita, Ioan-Octavian; Jennions, Ian K.; Irving, Phil

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Design for Diagnostics and Prognostics: A Physical-Functional Approach

Octavian Niculita
Integrated Vehicle Health Management Centre, Cranfield University, Cranfield, Bedford MK43 0FQ, UK
o.niculita@cranfield.ac.uk

Ian K. Jennions
Integrated Vehicle Health Management Centre, Cranfield University, Cranfield, Bedford MK43 0FQ, UK
i.jennions@cranfield.ac.uk

Phil Irving
Integrated Vehicle Health Management Centre, Cranfield University, Cranfield, Bedford MK43 0FQ, UK
p.e.irving@cranfield.ac.uk

Abstract— **This paper describes an end-to-end Integrated Vehicle Health Management (IVHM) development process with a strong emphasis on the COTS software tools employed for the implementation of this process. A mix of physical simulation and functional failure analysis was chosen as a route for early assessment of degradation in complex systems as capturing system failure modes and their symptoms facilitates the assessment of health management solutions for a complex asset. The method chosen for the IVHM development is closely correlated to the generic engineering cycle. The concepts employed by this method are further demonstrated on a laboratory fuel system test rig, but they can also be applied to both new and legacy hi-tech high-value systems. Another objective of the study is to identify the relations between the different types of knowledge supporting the health management development process when using together physical and functional models. The conclusion of this lead is that functional modeling and physical simulation should not be done in isolation. The functional model requires permanent feedback from a physical system simulator in order to be able to build a functional model that will accurately represent the real system. This paper will therefore also describe the steps required to correctly develop a functional model that will reflect the physical knowledge inherently known about a given system.**

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1. INTRODUCTION

The identification of component/sub-system failure that can lead to the loss of the entire system/platform functionality is a crucial activity in designing and commissioning high-tech, high-value systems. Early stage design phases have been proved to offer the most effective analyses for development of integrated vehicle health management (IVHM) solutions [1], [2] and [3] . Within the early design stages, various design alternatives can be explored, before costly decisions are approved [4].

In the past decade, a significant amount of research related to development of IVHM solutions focused on detection and isolation of component failures.

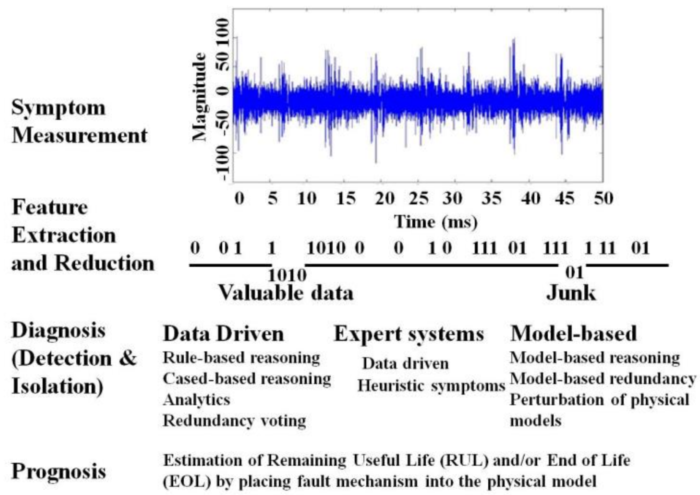

Figure 1- IVHM Development Process at the component level

In this paper, we developed several unique capabilities that were consolidated as an end-to end health management development process capable of handling the design of the IVHM capability at the system/platform level. The new process is an extension of the process depicted in Figure 1, by integrating design, safety and reliability analysis for the identification of optimized sensor set solutions/diagnostic rules. This new process is captured in Figure 2 and addresses the 'system of systems' IVHM design perspective.

The proposed end-to-end analytical framework consists of seven different layers: physical simulation, diagnostic analysis (functional decomposition and failure-symptom relation analysis), symptom measurement, feature extraction and reduction, diagnosis (detection and isolation) and prognosis.

Firstly, physical models (at the top of Figure 2) are the design system codes that are used by the OEMs to design a new components/sub-system/system. Secondly, a functional modeling approach was employed to be able to carry out functional failure mode effects and criticality analysis.

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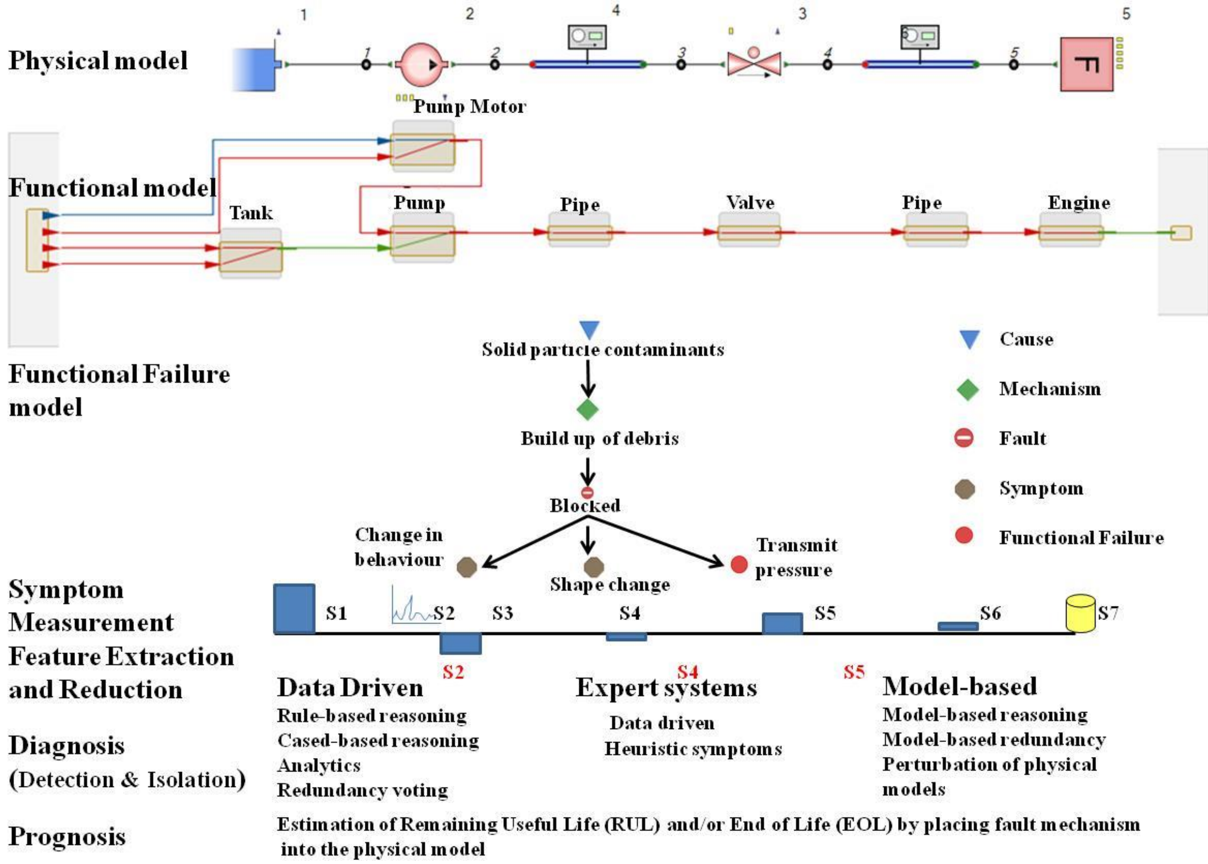


Figure 2 - IVHM Development Process at the system level

The third layer is represented by the failure mode analysis. The approach adopted here is supported by the functional failure. The functional failure mode, effects and criticality analysis (FFMECA) helps the identification in a systematic manner of various sensor set solutions capable of detecting and isolating the failure modes captured in the analysis. Trade studies must be carried out in order to identify the optimum sensor set solution based on weight, cost, reliability and sensitivity until initial health management requirements are met (fault detection requirements, fault isolation requirements, ambiguity group constraints). These sensor set solutions will be complemented by additional signal processing techniques.

The combination of physical-functional analyses produces accurate sensor set identification only if these types of analyses are tightly coupled. Both types of analyses represent different facets of the same system and must be cross validated in order to ensure an accurate representation of the real system in a simulation environment. In order to demonstrate the proposed end-to-end process, this paper analyzes the design of UAV fuel system health management solution. The challenges and opportunities of integrating the prognostic capability as part of this solution will be addressed towards the end of the paper.

The following sections present the proposed IVHM development process at the system level.

Section 2 summarizes the design related work as the foundation of the system design but also the foundation of the health management unit design. In Section 3, the details of the functional analysis approach are discussed including the verification and validation of a functional model.

The implementation and validation of various sensing solutions on a UAV fuel system is presented in Section 4. The results of end-to-end IVHM development process including an instantiation of this process using dedicated COTS software tools are presented in Section 5. Section 6 collates the concluding remarks and a summary of the future direction of this research.

2. FUEL SYSTEM TEST BED – PHYSICAL ANALYSIS

We aim to take a relative simple fuel system, to illustrate the key steps of the IVHM development process using a mix of physical-functional analysis and to implement the output of these analyses within an IVHM solution that meets the specific fault detection and isolation requirements (100% fault detection and 100% fault isolation). A schematic diagram of the fuel system is presented in Figure 3. A few modifications were added to this initial schematic in order to be able to physically simulate the degradation of five components (the filter, the pump, the shut-off valve, the pipe connecting the shut-off valve to the sump tank (our virtual engine), and the nozzle). These adjustments translate into Figure 4. The fuel system contains a motor driven external gear pump with internal relief valve, a shut off valve, one filter, two tanks (main tank and sump tank, the last one emulating the engine), non-return valve, three-way valve to switch between recirculation and engine feed mode, nozzle to simulate engine injection and back pressure when partially closed. Figures 3 and 4a present only the engine feed scenario. The fuel system is representative of a small UAV engine feed. The design of the IVHM capability will focus on the filter, pump, shut-off valve, pipes and nozzle failure modes. Five failure modes that are emulated on the rig are: filter clogging from foreign matter, pump degradation, valve stuck in a midrange position, a leak in the main line, and a clogged nozzle.

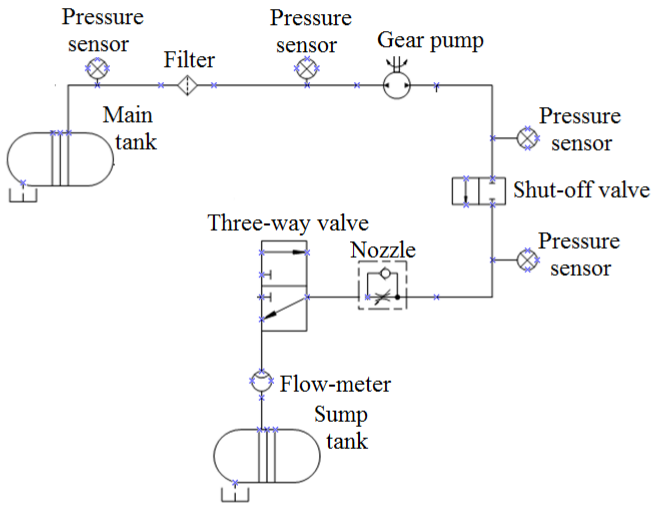


Figure 3 - IVHM Centre fuel system demonstrator

The fuel rig can accommodate various faults with different degrees of severity. When a filter clogs, the flow through the filter reduces and the pressure difference measured across the filter increases. The filter failure was emulated by replacing the filter component with a Direct-acting Proportional Valve (DPV1). Valve position fully open is equivalent to a healthy filter; partially closed being equivalent to a clogged filter with a particular degree of severity. Various degrees of severity of this fault can be simulated by varying the DPV position. In this manner, incipient, slow progression, cascading and abrupt types of faults can be simulated on the rig and the ability of the functional approach to model and address such conditions can be assessed. The physical implementation of the fuel system test bed is depicted in Figure 5.

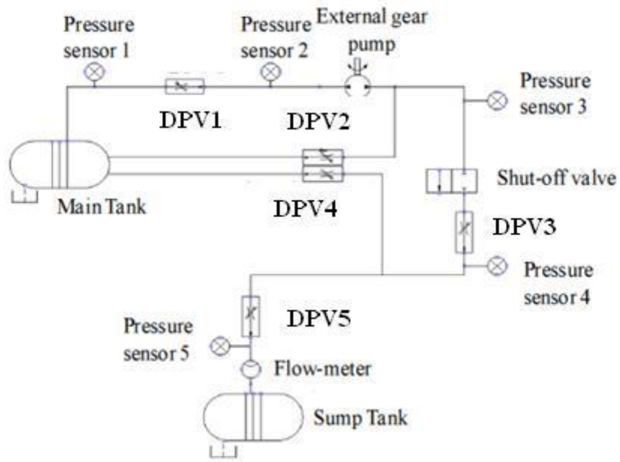


Figure 4 - Fuel delivery system demonstrator including degradation mechanisms

Figure 5 - Fuel system test bed

The physical system allows the testing and validation of various IVHM models and the assessment of the analyses carried out using such models that will be employed for the implementation of the proposed end-to-end IVHM development process. Prior the construction of the physical system, a physical simulation model was developed during the fuel system design phase using a CAE COTS software tool: SimulationX™ from ITI [9] (Figure 6). This modelling phase encompasses basically the sensibility studies carried out during the fuel system design phase in order to specify in a correct manner the components/system performance in order to meet the specified system requirements.

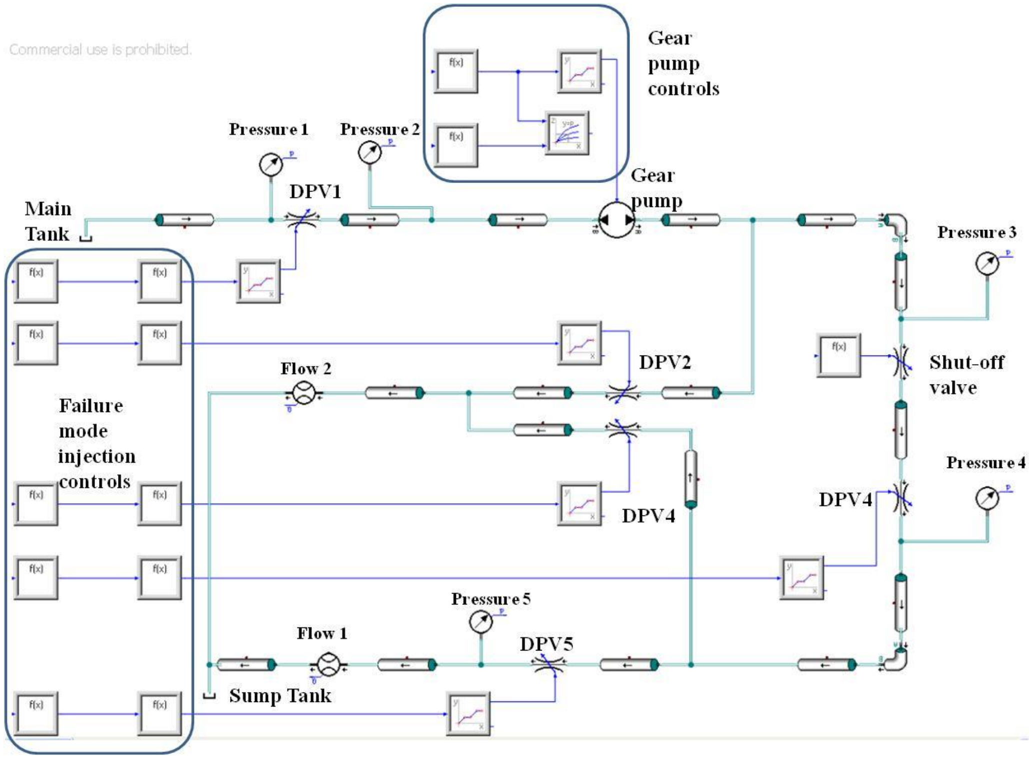


Figure 6 - SimulationX™ model of the fuel system test bed

Pipes' length and diameter, pump characteristics, loss coefficient versus valve opening characteristics, shut-off valve pressure drop when fully opened, tank's capacity have been identified within the design phase by carrying out various scenarios in a controlled simulation environment. Volumetric flow rates in the mail line and pressure rates at five different locations were calculated using the physical model. The results produced using the SimulationX™ physical model are presented against the test rig data for both: normal and abnormal conditions (one of the five faulty cases).

For the healthy state of the fuel system, the direct acting proportional valves were set as follows: DPV1 – fully open, DPV2 – fully closed, DPV3 – fully open, DPV4 – fully closed and DPV5 – fully open. Pressure and flow rates for the healthy condition were recorded for a period of 10 minutes in order to have a good estimation and pump rotational speed was set at 400rpm. A series of 11 samples were taken using the conditions mentioned above. The feedback loop of the pump control unit was active, so the pump speed was constant for the entire testing session.

The volumetric flow rates obtained by running both the rig and the simulation model for healthy conditions are presented in Figure 7. This shows a small discrepancy between the mean of the measured data and the SimulationX™ predictions of less than 1%. Pressure rates calculated using SimulationX™ at locations 1, 3 and 4 follow exactly the profile offered by the pressure sensors fitted on the rig at the same locations (having less than 3% error difference) (Figure 8).
For the locations 2 and 5 the error is less than 6.5%, being also a clear indication that pressure drop across the DPV valve is greater in reality than in the model when valve is fully opened.

The SimulationX™ fuel system model returned results very close to those obtained on the rig when using the same configuration for almost the same pump speed under different operating conditions (difference between the averaged pump speed on the test rig and the set value of the pump speed in the model being less than 0.01%).

Figures 9 and 10 quantify the error between the model output and test rig readings for pressure at five different locations and volumetric flow rates at different pump speeds for steady state conditions (100 rpm, 200rpm, 300 rpm, 400 rpm and 500 rpm).

Volumetric flow rates were simulated by the model with an error less than 1.75% (errors values are labeled with V in Figure 9). Pressure values calculated by the model at locations P1, P3 and P4 are less than 3.5% error compared with the values from the rig. A slightly bigger difference is observed in two of the pressure rates (measured at location P2 and P5), the test rig sensors returning values with less than 6.2% different than the model output (errors values are labeled with P1, P2, P3, P4, P5 in Figure 10).

The model was calibrated using data obtained on the rig since the majority of the components are low cost type of components and hence the manufacturers' data is not available.

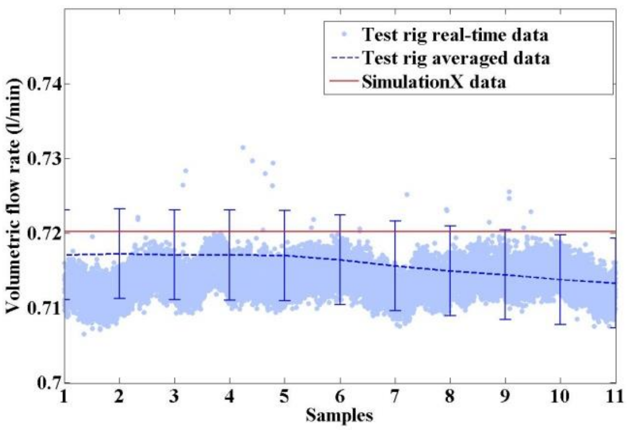


Figure 7 - Model results vs. test rig data for the fuel system – volumetric flow rate

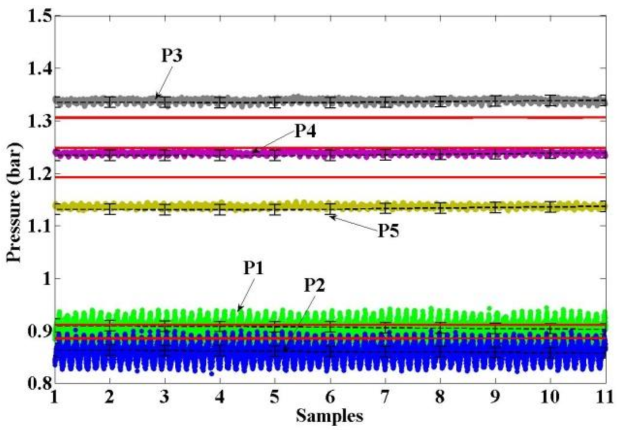


Figure 8 - SimulationX™ results vs. test rig data for the fuel system – pressure rates

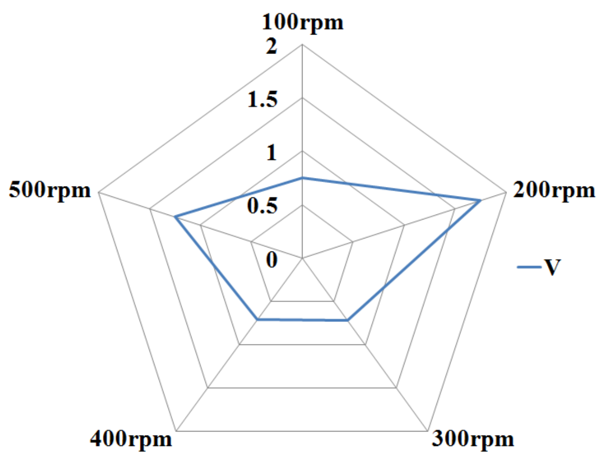


Figure 9 - Error between the simulated volumetric flow rates vs. test rig readings in %

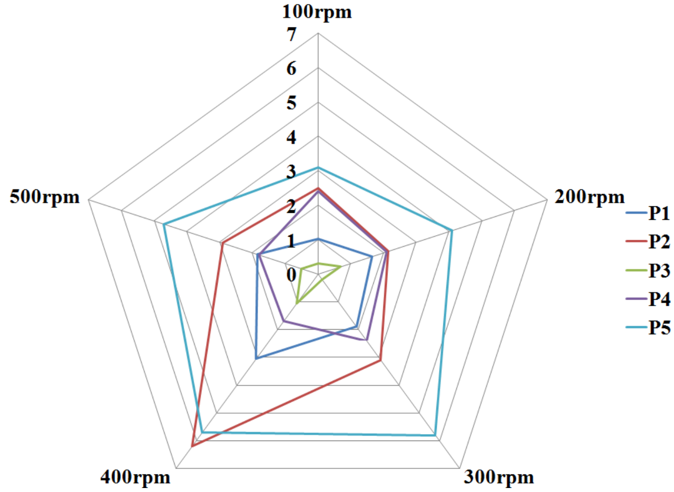


Figure 10 - Error between the simulated pressure rates vs. test rig readings in %

The same assessment (Model vs. Physical system) was done for each individual faulty case. This allows the system designers to provide the correct information to the IVHM designers regarding the behavior of the system outside the normality envelope.

The IVHM design process must be considered as part of the system design if the business models of OEMs are changing from supplying products to service offerings (e.g. GoldCare™ from Boeing, TotalCare™ from Rolls-Royce, Trucknology™ from MAN, etc.). The proposed IVHM development process will reveal the fact that the IVHM design process has the roots in the system design and the physical models will be used as a baseline throughout the entire process for verification and validation of other models and analyses [3].

The initial system design phase described in this section that is supported by physical models covers the top layer of the end-to-end IVHM development framework.

3. FUNCTIONAL ANALYSIS

The second step of the proposed approach is based on the concept that a failure happens when the function of a specific component/sub-system/system is not fulfilled. This translates automatically into a malfunction at the component/sub-system/system level.

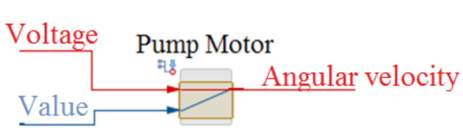
The use of system functional analysis as part of the system design can enhance the confidence of safety analysis at the early stages and aid throughout the development of system health management capability. Health management design is generally undertaken in order to support fault detection strategies, fault isolation strategies and design of testability solutions. Fault detection analysis calculates the percentage of system faults that can be detected by defined tests. Fault isolation analysis determines the failure ambiguity groups that will result from exercising the defined tests over the fault universe. Testability analysis sometimes associated with sensor set definition and optimization will determine the optimal sequence of tests to be implemented based on the fault space, defined tests, and other optimization criteria (practicality, cost, weight, reliability). As designs become more complex, defining and implementing a testability solution becomes more challenging. Ideally, health management capability must be developed concurrent with the design itself. Current practice does not facilitate an automatic feedback loop between test engineers and system design engineers. This feedback can be achieved through the incorporation of health management development process in the early design stage of the asset.

The functional modelling approach uses functions and flows to describe the system. Clear ontology should be provided with each functional model in order to ensure others can read it, as they might represent a blueprint of the system using a different ontology.

Functional modelling makes use of a system model which decomposes the main system function(s) into smaller functions which are well defined for each component. This enables the assessment of the correct functionality of the system, but also allows the investigation down to the component/part level.

MADe™, a COTS software tool produced by PHM Technology, was employed to deal with functional analysis as part of the IVHM development process, leveraging also the conceptual design, safety, reliability and initial sensor set optimization phases within the development of a new product [10]. A primary element of any functional modelling approach is the representation of real world information corresponding to the input and output elements for the previously defined functions. These elements are represented by flows: material, signal and energy [5]

Figures 11 and 12 are two snapshots of the fuel delivery system functional model. Figure 11 describes the functionality of the pump motor underpinned by input and output flows: to convert the electric energy and a specific analogue value into mechanical rotational energy. Components can be fully described following this functional approach by a single function (e.g. gear pump motor) or a combination of function (see the shut-off valve functions) as described in Figure 12 (to channel and to regulate the fluid from inlet to outlet).



To convert – to change from one form of energy (*electrical energy*) or material to another form of energy (*mechanical – angular velocity)*

Figure 11 - Functional model schematic for gear pump motor component

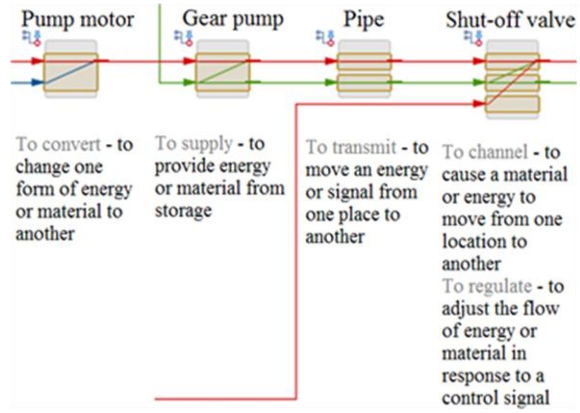


Figure 12- Functional model schematic for gear pump motor, gear pump, pipe and shut-off valve components

Figure 13 presents the full functional model at the system level and also presents the exchange of information between components using specific types of flow.

The reticence in using this tool is the fact that requires a change in failure addressing approach from physical to functional. Therefore it requires a fully adoption of its functional taxonomy in order to be able to emulate the real system into viable models and to complete the second step of the proposed IVHM development process. It was mentioned that functional analysis can liaise various type of analysis carried out during the initial design stages (conceptual design, safety analysis and reliability analysis). Using MADe™ tool, these type of analyses are performed using the same functional model (similar to the one defined in Figure 13) [3], [6]. Fault tree analyses (FTA) and functional failure effects and criticality analyses (FFMECA) can be carried out once failure mode diagrams are defined. Failure mode diagrams represent the connection between cause(s)-mechanism(s)-fault(s)-symptoms(s) and functional failures.

For example: a pipe component can leak or be clogged. These two failure modes are captured by the behavioural taxonomy as shown in Figure 14. Causes are linked to mechanisms, which then lead into faults that are ultimately connected to functional failures.

Mechanisms and faults can present particular symptoms and these are captured accordingly in the failure diagram. These symptoms are the expression of unintended/emerging behaviour of a faulty system. Due to the restrictions of the physics for this failure mode, the output flow indicating the normality of the pipe's function can display either OK or too low, hence the negative causality between the fault concepts and the functional failure concept.

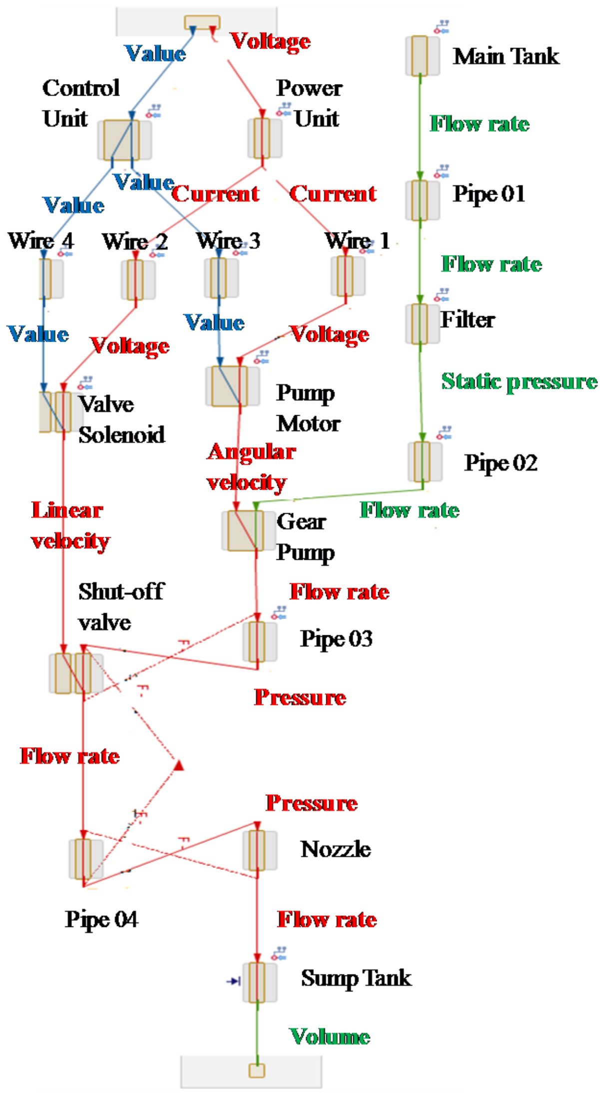


Figure 13 - Fuel system functional model

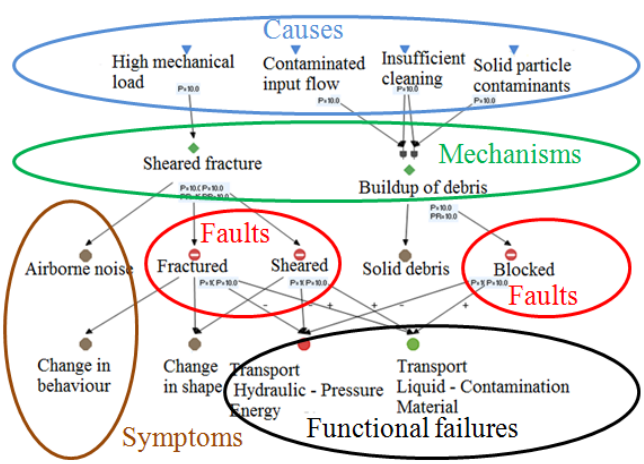


Figure 14 - Failure mode diagram, pipe example

Failure diagrams can be defined only for specific components for which it is required to implement IVHM capabilities, or for all components of the systems. The selection of the most critical components will be then be made by adding criticality indicators to all components (detectability, severity and occurrence) and by filtering only the components with a risk priority number above a specific threshold.

Using the functional approach, sensor set solutions can be identified (selection of sensors that monitor the functional flows for the components selected for IVHM analysis). The qualitative characteristics of each individual failure contained in the propagation table (a collection of the effects of a functional failure on the other components of the system) are processed by an optimization algorithm in order to identify the combination of elements which allow discriminating between them. The elements mentioned above are in fact the flows captured in the functional analysis and the type of flows will determine the type of sensors to be used to identify a particular fault. A detailed description of the sensor set discrimination analysis using this software is presented by Rudov-Clark (Rudov-Clark, 2009).

Functional analysis is a qualitative analysis. This type of qualitative analysis identifies the foundation of an IVHM solution for a given system for a known fault universe. As mentioned in the previous section, for this particular scenario of the fuel system, the fault universe is composed by five distinct faults. The optimization algorithm generates 6 sensor set solutions, with maximum coverage and no ambiguity groups. One of the solutions contains four sensors and is presented in Figure 15 and it comprises of:

S1 - one sensor measuring the *static pressure* after the Filter,
S2 - one sensor measuring the *flow rate* after the Gear pump,
S3 - one sensor measuring the *flow rate* after the Shut-off valve
S4 - one sensor measuring the *pressure* in the Pipe 04.

It is important to understand the system behavior and the failure mechanism of different abnormal conditions at the initial stage of the health management design. Initially, the test bed was fully populated with sensors in order to get as clear as possible image of the signature of each individual type of fault. This supplemented the system designer knowledge regarding the system behavior under faulty conditions.

Fault signatures were obtained by running the rig and the simulation model under five faulty scenarios: i) clogged filter, ii) degraded gear pump, iii) shut-off valve stuck in various interim positions, iv) leaking pipe, v) clogged nozzle. A propagation table containing the symptom vectors corresponding to each type of fault injected in the system is described Table 1.

Each vector contains the system deviation from the healthy condition in terms of pressure in various points and volumetric flow rate in the main line. Each fault is characterized under low (marked with orange) and high (marked with red) degrees of severity. Each line in Table 1 represents a qualitative expression of the quantitative simulation output for a scenario describing a particular failure mode of the system.

The analysis was carried out during the initial design phase of the fuel system for all five faults taking in account various severities of the fault. The first line of the Table 1 reflects the scenario of normality. Each sequential two lines reflect the system behavior under an abnormality scenario (line 2 - clogged filter, low to medium severity, line 3 – clogged filter, high severity). It is widely accepted that simulation models are a good starting point for the identification of the barrier between normal and abnormal behavior of a system under known operating conditions.

The information forming Table 1 has been extracted from the translation of the quantitative type of information offered by the physical simulations into a qualitative domain. The translation of the qualitative layer into quantitative means for the degradation phenomena of a clogged filter is represented by the probability density functions for the data offered by pressure sensors at various locations. Compared to the discrete values, offered by the SimulationX™ model, the data provided by the real system in real conditions are generally scattered around the simulated values.

The histograms of the data sets obtained on the test rig represent the sum of the effects of the environmental conditions, manufacturing tolerances, sensor accuracy and resolution, system noise levels, etc. The assessment of the system behavior under faulty conditions was initiated during the first layer of the proposed IVHM development process. The profile of each row corresponding to a unique type of fault was matched by the qualitative information offered by the functional models developed in the second layer of the proposed process.

Table 1. Fault signatures – qualitative propagation table

	Q	P1	P2	P3	P4	P5
Healthy Configuration	↔	↔	↔	↔	↔	↔
Clogged filter Low/Medium severity	↓	↑	↓	↓	↓	↓
Clogged filter High severity	↓	↑	↓	↓	↓	↓
Degraded pump Low/Medium severity	↓	↓	↓	↓	↓	↓
Degraded pump High severity	↓	↓	↓	↓	↓	↓
Degraded valve Low/Medium severity	↓	↑	↑	↑	↓	↓
Degraded valve High severity	↓	↑	↑	↑	↓	↓
Leaking pipe Low/Medium severity	↓	↓	↓	↓	↓	↓
Leaking pipe High severity	↓	↓	↓	↓	↓	↓
Clogged nozzle Low/Medium severity	↓	↑	↑	↑	↑	↓
Clogged nozzle High severity	↓	↑	↑	↑	↑	↓

A translation in the real world of rows 2 and 3 (including other two different degrees of fault severity – low severity and medium to high severity) from Table 1 for pressure parameters P1 to P5 is captured by Figure 16.

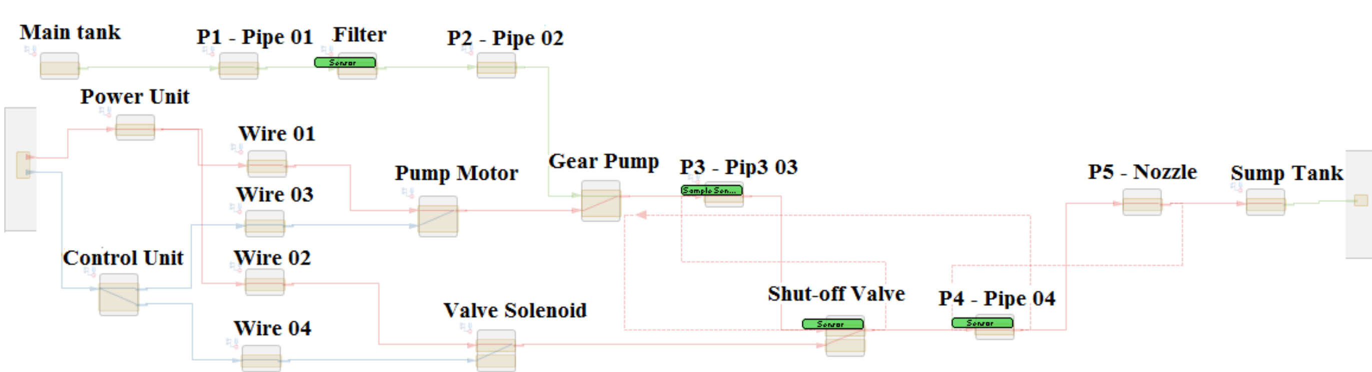


Figure 15 - Optimized sensor set identified using MADe™ functional analysis

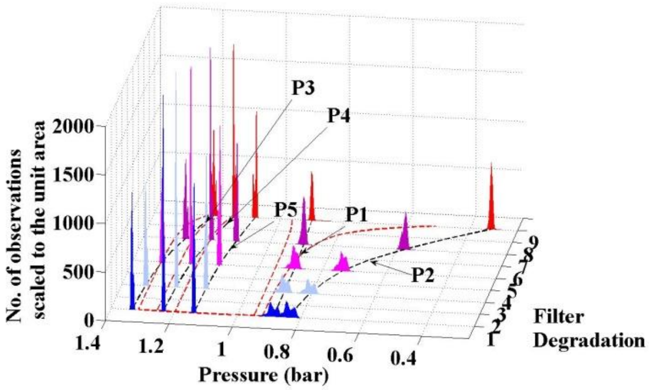


Figure 16 - Simulation vs. test rig results: Pressure rates at five different locations for different fault severities

The functional analysis described so far allowed the implementation of the second and the third layer of the proposed process, but it also enabled the analyses supporting the fourth layer of the process: identification of the symptom vectors (the combination of measurements that allow the identification and isolation of the faulty components). This type of analysis must support trade-off investigations that allow the IVHM designer to approximate the initial costs weight, reliability of the health management capability (Figure 17).

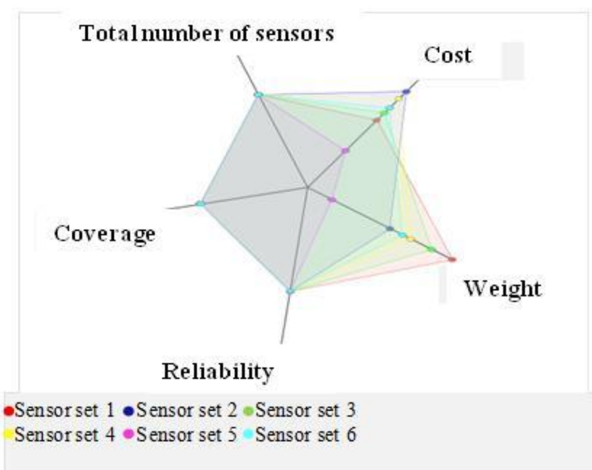
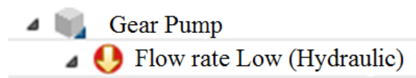


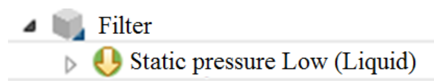
Figure 17 - Sensor set query – MADe analysis

4. DIAGNOSTICS AND PROGNOSTICS - IMPLEMENTATION AND VALIDATION

Based on the analyses described in the previous sections, the IVHM designer has information about the location of these sensors contained in each sensor set, but also about the information regarding the type of flow monitored. All sensor set solutions are complemented by fault detection, fault isolation and ambiguity group indicators. Also, each sensor set contains the diagnostic rules which will need to be implemented on the asset. A snapshot of the diagnostic rules associated to the sensor set solution from Figure 15 is captured in Figure 18. The qualitative diagnostic layer produced by MADe will have to be complemented by the quantitative layer obtained in the physical simulation of the system. Most of the time, the diagnostic rules are associated with the tests that need to be carried out during the diagnostic phase.



IF Sensor [Shut-off Valve] Flow rate is Low AND Sensor [Pipe03] Pressure is Low AND Sensor [Filter] Pressure is Nominal THEN failure mode on [Gear Pump] Flow rate Decrease



IF Sensor [Filter] Static pressure is Low, THEN failure mode is Filter - Static Pressure- Decrease

Figure 18 - Diagnostic rules for the optimized sensor set solution

The information generated by MADe™ software can be used in this manner by the IVHM designer in developing the IVHM solution but also by the system designer as well, the last one having the opportunity to analyze the impact on the overall design once this solution is integrated on the asset. The integration of the HM solution on the asset might require additional updates to the original design, therefore safety and reliability analyses will have to take into consideration the IVHM sub-system characteristics.

As described in Figure 18, the diagnostic rules evaluate specific parameters by quantifying their deviation from normality (Very Low, Low, High or Very High). When specific conditions are met, the corresponding alarm for a particular failure is triggered. The sequence of diagnostic rules acts as a diagnostic engine shaped as an expert system. Alternatively to an expert system, the optimized sensor set can be linked with a dedicated model-based reasoner.

In general, expert systems perform extremely well in specific conditions, mainly in the case of high severity cases. Let's take the example of the clogged filter. According to the second rule in Figure 18, high severity cases and medium severity cases can be easily detected without any risks of false alarms (Figures 19 and 20).

In both, Figure 19 and Figure 20, for the data obtained under normal conditions (marked with blue), average, average±2*σ and average±3*σ thresholds have been highlighted. These statistical thresholds ensure a 95% and respectively 99.7% of the normal data is positioned within these limits. The diagnostic rule associated with the case of a clogged filter will offer maximum efficiency for these two types of scenarios (or any other scenarios with a degree of severity between mid severity and high severity).

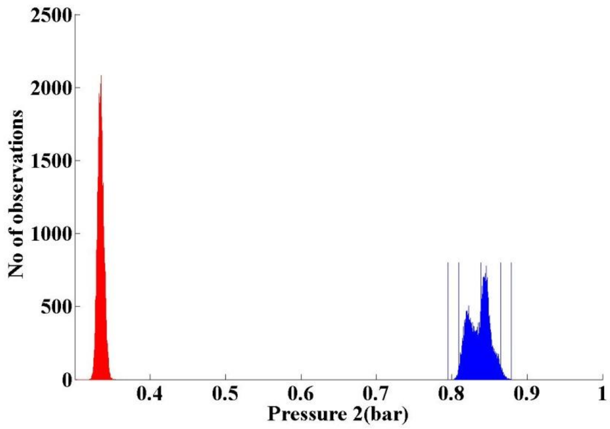


Figure 19 - Clogged filter – Example of high severity scenarios

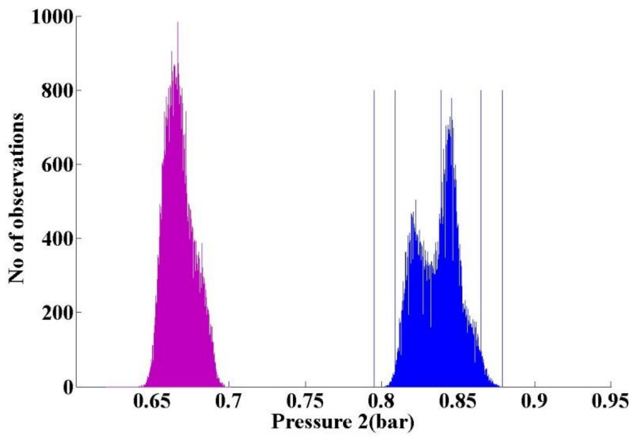


Figure 20 - Clogged filter – Example of medium severity scenarios

The situation is changing when IVHM requirements mandate the detection of lower severity cases. For these cases, there is a clear overlap between the data obtained under faulty conditions and the data obtained under healthy conditions. Figure 21 show a degraded scenario characterized by a medium to low level severity while Figure 22 depicts a very low level of severity for the same clogged filter case.

These particular cases are characterized by a high risk of false positives and false negatives, and therefore additional signal processing techniques are required. These techniques are formerly known as feature extraction techniques and will form the base of the fifth layer of the proposed IVHM development process.

Unsupervised learning techniques like K-means, K-medians, Fuzzy C-means, Gaussian Mixture Models (GMM), Hierarchical Clustering, Spectral clustering, Vector Quantization, Self-Organizing Maps (SOM) can be applied for the identification of faulty data. For the lowest severity faulty case that can be simulated on the test rig for a clogged filter scenario (data presented in Figure 22), a two-component Gaussian Mixture Model (GMM) was fitted. As input data for this model, the average and standard deviation values (calculated for every second) were used. A basic clustering technique has been used to separate the faulty from the healthy data.

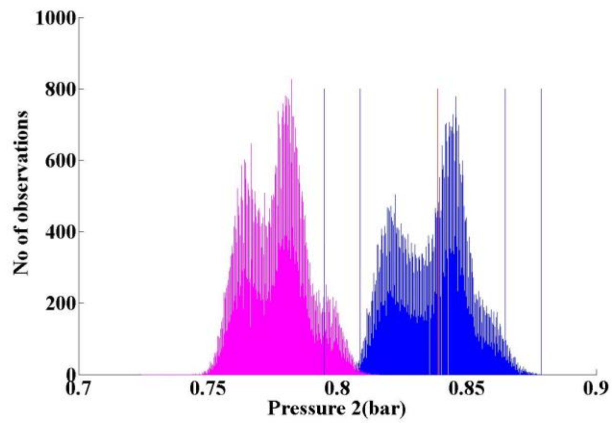


Figure 21 - Clogged filter – Example of medium to low severity scenarios

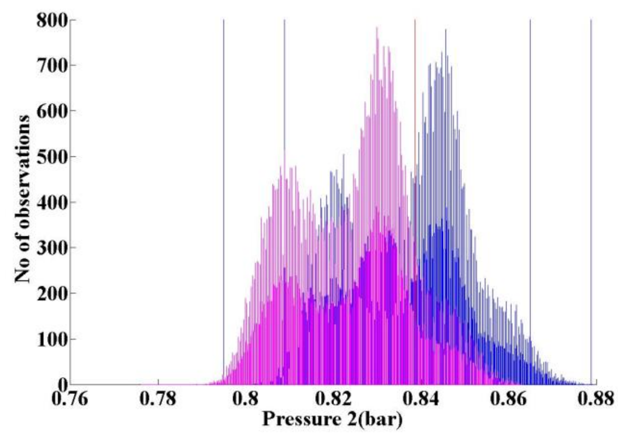


Figure 22 - Clogged filter – Example of very low severity scenarios

As a verification technique, the posterior probability was computed. This correlation was calculated for these two components in order to ensure a clear separation between the healthy/faulty clusters (Figure 23). The probability density functions associated to the Gaussian Mixture Models are depicted in Figure 24.

Supervised learning techniques can also be implemented when additional data characterizing the 'normality' is obtained from service.

Diagnostics can be performed using the sensors identified through the physical-functional analysis by making use of the diagnostic rules previously described. These diagnostic rules will use as thresholds the values indicated by the physical 'models of normality' (developed within the design phase) in combination with additional signal processing techniques (as described in the previous paragraphs). At this point there is no exact information regarding the transition time from normal state to faulty conditions). This transition has to be determined through physical simulations of the asset under faulty conditions.

Various studies focused on simulation of the degradation for specific components and not for the entire platform (Daigle and Goebel, 2011). To predict the Remaining Useful Life (RUL) prognostic techniques are needed. This layer of the proposed approach is still in its early days but the prognostic algorithms will have to rely on the simulations performed within the design phase (physical layer of this framework) completing the picture.

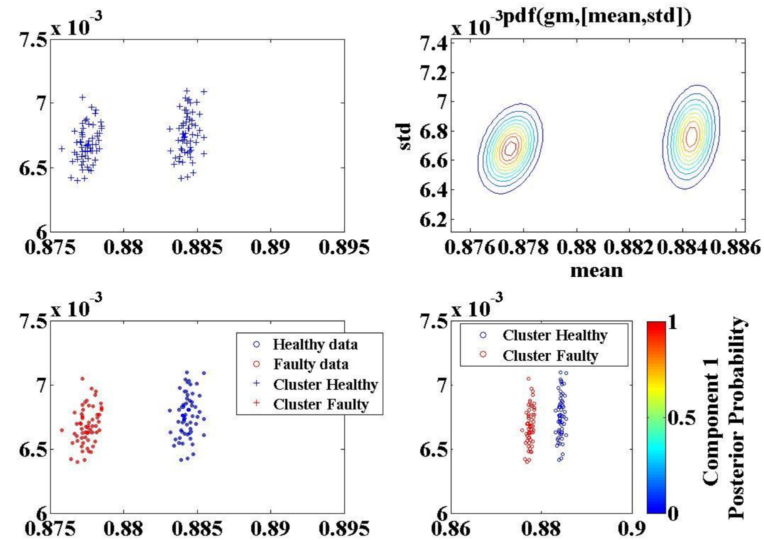


Figure 23 - Clogged filter – Feature extraction techniques

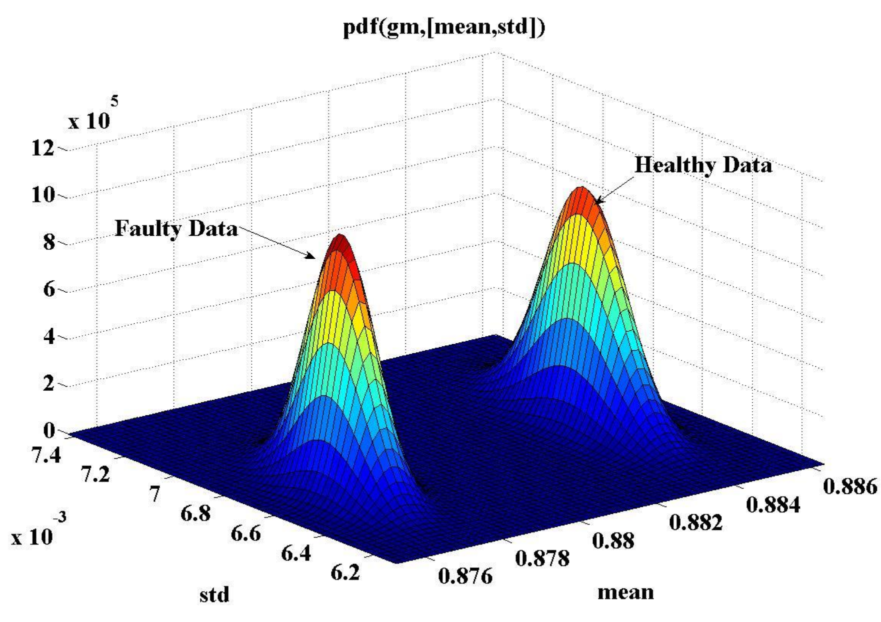


Figure 24 - Clogged filter – PDFs for the Gaussian Mixture distributions

5. END-TO-END IVHM DEVELOPMENT PROCESS – A COTS SOFTWARE VIEW

This section discusses the previously described end-to end IVHM development process by emphasizing the COTS software tools used during the implementation and also highlighting the connections with various stages of the generic engineering cycle. A different view of the IVHM development process from Figure 2 is presented in Figure 25.

The central circle is the usual engineering design cycle, from design through realization and into service and maintenance. The outside cycle is populated with the tools and the models that were employed for the parallel design of an IVHM system. The physical simulations are developed during the engineering design of the component/sub-system and system level. In our case the physical models have been developed using SimulationX™.

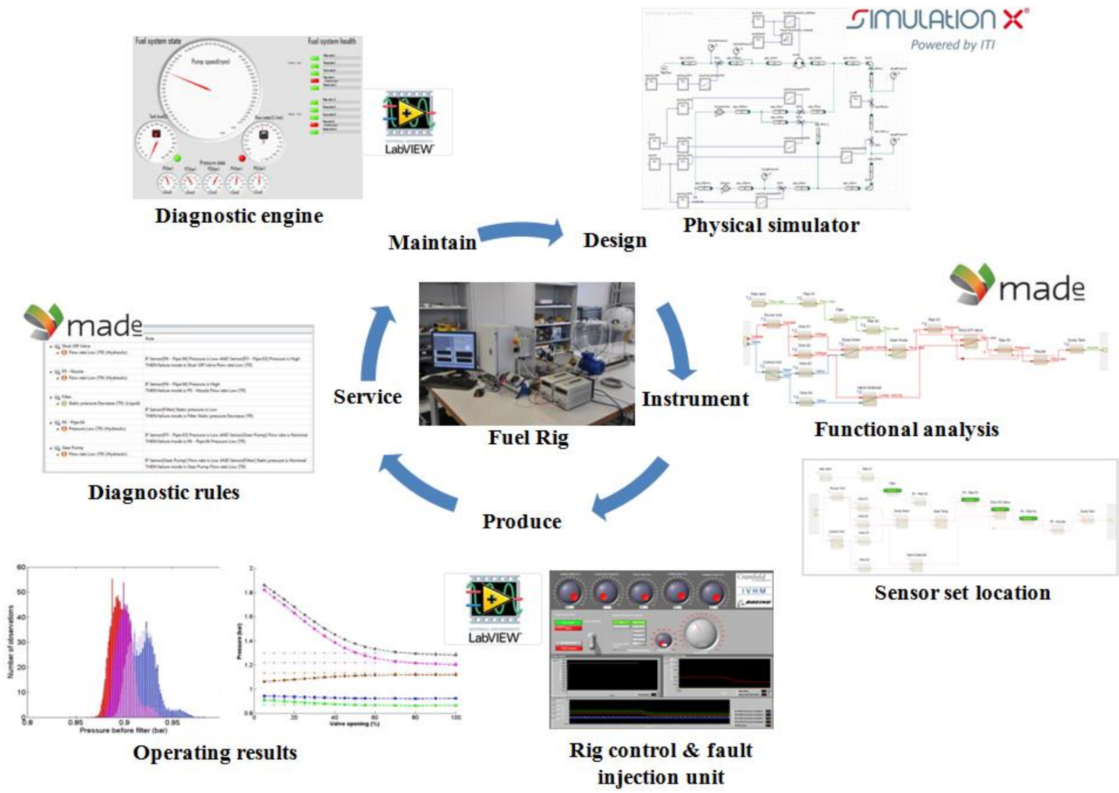


Figure 25 - COTS software tools used for the implementation of the IVHM development process

The development of the physical modeling phase is complemented by a functional analysis which aids safety, reliability and testability analyses (sensor set identification and diagnostic logic associated with a specific sensing solution). For these purposes, MADe™ software was used and six sensor set solutions that provide 100% fault detection and isolation were generated.

The integration of the sensing capability on the real asset is performed in the next phase (prototyping/production) using tools like Labview™ [11]. This integration phase employed the interrogation of the dll file associated to the physical model in order to obtain an IVHM solution that works under various operating conditions. Sensitivity and calibration studies are carried out in order to identify the thresholds that ensure a good separation of the faulty cases, with a reduce number of false positives and false negatives alarms.

Once the system is deployed in service, the MADe™ diagnostic rules or dedicated model-based reasoners can work on real-time or can be packaged for the maintainer for troubleshooting purposes.

Data collected by the maintainer should be also used for the maturation of the existent systems/development of the new systems' generation.

Further research will investigate means to capture the IVHM legacy information and knowledge into future engineering designs.

6. CONCLUDING REMARKS

We presented a process for development of a health management capability for high-tech, high-value assets. The process was demonstrated on a UAV fuel delivery system test bed and is considered to be generic enough to be applied to other types of complex systems. We defined a set of layers and the specific analysis that has to be carried out within each of these layers.

The baseline for the system design and also for the health management design is represented by the physical analysis. A very good understanding of the physics is required to run both design activities. Physical analysis was complemented by the functional analysis in order to represent a different dimension of the same system. This allowed us to approach the failure mode analysis phase from a functional perspective. This approach makes the assumption that a component/system fails when its function doesn't meet the design specifications. Functional FMECAs were carried out using specific tools and the output of this analysis created the premises for sensor set identification.

The mix of physical and functional analysis is generally employed during the conceptual/initial design stages allowing space for various re-design/re-configuration decisions before the beginning of the detailed design phase. The most suitable sensor set candidate (based on cost, reliability, weight, accuracy) was integrated on the asset and calibration procedures were carried out to quantify the effectiveness of the diagnostics capability. After being fully prototyped/deployed in service, the health ready system will be further used to obtain data that will enhance the diagnostics/prognostics and will provide an accurate representation of the degradation phenomenon under various operating conditions. The initial attempt to describe the degradation curves associated to the critical components/sub-systems will have to be based on the same engineering knowledge collated in the physical models developed during the design phase.

For the demonstration task of this project, only commercial-of-the-shelf software tools were employed (SimulationX™ for multi-domain simulations, MADe™ for functional analysis, sensor set identification and optimisation and diagnostic rule generation and Labview™ for the implementation stage).

As future work, models of the degradation phenomenon for the five fuel delivery type of faults will be developed and integrated in the physical layer of the proposed framework.

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BIOGRAPHY

Octavian Niculita *gained his BSc in Automation Control and Computer Science (Technical University of Iasi, Romania). He undertook his PhD research at TUIASI, Romania and at the University of Ferrara, Italy as part of the European Doctorate of Sound and Vibration Studies program. He has been a Research Fellow with Integrated Vehicle Health*

Management Centre, Cranfield University, UK, since 2009, being actively involved in the first project of the centre regarding evaluation of COTS software tools employed throughout the health management development process and also transformation of state-of-the-art diagnostic tools into state-of-practice. His current research interest focuses on IVHM design techniques, IVHM deployment, implementation and testing of real-time frameworks for fault diagnosis and fault prognosis.

*Professor **Phil Irving** gained his BSc and PhD at Birmingham University. In the early 1970s he joined the very active fracture mechanics research group at Birmingham, performing some of the earliest measurements of fatigue crack growth thresholds in metallic materials. In 1973 he moved to the National Physical Laboratory where he developed techniques for determining stress corrosion cracking behaviour of steels in high pressure hydrogen gas environments, and continued with exploration of factors controlling fatigue cracking in high strength steels. In 1978 he began work at GKN Technology, the research and development organisation of the GKN Automotive group, where for the first time he became involved in putting his knowledge of fatigue and fracture to practical use in design and service life prediction of a wide range of automotive components. As well as working with traditional steels, cast irons and aluminum alloys, he also played a significant role in the development of the GKN glass-epoxy leaf spring. In 1991 he moved to Cranfield, accepting a CAA sponsored Chair in Damage Tolerance. In the time since then he has worked extensively on fatigue fracture and damage tolerance in helicopters and fixed wing aircraft. A continuing theme has been research into techniques and benefits of structural health monitoring to structural integrity of aircraft. This interest lead to his close involvement in the setting up of the Cranfield Integrated Vehicle Health Management (IVHM) Centre and his pursuit of IVHM and SHM research within the centre. He is a Chartered Engineer and a Fellow of IM3.*

*Professor **Ian K Jennions**'s career spans over 30 years, working mostly for a variety of gas turbine companies. He has a Mechanical Engineering degree and a PhD in CFD both from Imperial College, London. He has worked for Rolls-Royce (twice), General Electric and Alstom in a number of technical roles, gaining experience in aerodynamics, heat transfer, fluid systems, mechanical design, combustion, services and IVHM. He moved to Cranfield in July 2008 as Professor and Director of the newly formed IVHM Centre. The Centre is funded by a number of industrial companies, including Boeing, BAe Systems, Rolls-Royce, Thales, Meggitt, MOD and Alstom Transport. He has led the development and growth of the Centre, in research and education, over the last three years. The Centre offers a short course in IVHM and the world's first IVHM MSc, begun in 2011. Ian is on the editorial Board for the International Journal of Condition Monitoring, a Director of the PHM Society, contributing member of the SAE IVHM Steering Group and HM-1 IVHM committee, a Fellow of IMechE, RAeS and ASME. He is the editor of the recent SAE book: IVHM – Perspectives on an Emerging Field*